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Big Data and Fuzzy Logic for Demand Forecasting in Supply Chain Management: A Data-Driven Approach

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Abstract

Demand forecasting is an important activity that directly impacts the supply chain's functioning, offering a solid foundation for decision-making. The operational strategy has long focused on demand forecasting to manage inventories better and maximize customer satisfaction. However, most demand forecasting methods fail to reveal anything to businesses since they don't account for product seasonality, current market trends, or how forecasting affects the bullwhip effect. There is a pressing requirement to establish technologies capable of intelligently and swiftly examining massive amounts of data in the supply chain. Big Data may assist firms in resolving their issue. At the same time, Fuzzy Logic models help capture and manage uncertainty in situations lacking historical data, subjective consumer preferences, or unpredictable market circumstances. Hence, this paper proposes a Fuzzy Logic based Big Data Driven Demand Forecasting framework (FL-BDDF) that determines the role promotional marketing efforts, past demand, and other variables have in making predictions that can shape, sense, and react to actual consumer needs. With Big Data Analytics (BDA), businesses may enhance the accuracy of their demand forecasts. Fuzzy Logic lets them include qualitative indications like market sentiment, expert views, or subjective risk assessments with the typical quantitative information. Operations and Supply Chain Management (OSCM) is like any other field, providing several chances to create enormous amounts of data in realtime. This study's results may help academics and industry professionals better grasp the possibilities presented by Big Data for SCM and demand prediction. The experimental outcomes illustrate that the suggested FL-BDDF model increases the accuracy ratio by 98.4%, the supply chain forecasting ratio by 97.3%, the customer satisfaction level by 95.4%, and reduced cost by 57% compared to other existing models.

Keywords: Supply chain management, Fuzzy logic, Big data, Demand forecasting, Data driven.

1 | Introduction

Companies in today's competitive market must improve their services' availability, dependability, and efficiency to stay in business. Accurate sales forecasts and well-planned demand enhance the efficiency of a

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supply chain [1]. Demand planning aims to assist decision-makers in sales, manufacturing, distribution, and procurement by creating a prediction model. Various organizational units at different planning levels use forecasts as the foundation f0/or their action plans. Usually, managers rely on their impressions and past experiences to forecast sales [2]. It is challenging to consistently receive trustworthy opinions from competent and experienced managers, which could differ from person to person. Consequently, precision marketers have relied heavily on forecasting models to learn about and meet the demands of their target audience. As a result, product Supply Chains (SC) increasingly focus on consumer behaviour and preference analysis using projections derived from customer data and their transactions [3], [4].

The primary goal of SCM is to manage the interdependent entities and activities that transport products, services, and data from their places of origin to their final consumers. The three recognized parameters of SCM concerns are capacity, demand, and cost. Nevertheless, there are uncertainties in practice due to changes in client demand, transportation of goods, organizational risks, and lead times [5], [6]. Uncertainty about future demand impacts SC performance most and has far-reaching consequences for transportation, inventory planning, and production scheduling. Thus, demand forecasting is essential for dealing with supply chain uncertainty [7].

The significance of Big Data Analytics (BDA) is further underscored by the introduction of Blockchain technology to enhance SC monitoring and the digitalization of supply networks overall. Due to the large number of products, suppliers, and consumers, as well as the high volume and velocity of transactions processed across supply chain networks, the data generated at various points in the chain is multi-dimensional and used for a wide range of purposes (e.g., supplier capacities, products, shipments, orders, retailers, customers, etc.) [8], [9]. Smart predictions that can learn from historical information and adapt to forecast the ever-changing demand in SC have replaced traditional statistical demand-predicting methods that rely on determining statistically meaningful patterns in historical data as measured by mean and variance attributes. This capacity is built upon top of significant data analytics approaches that uncover the fundamental linkages among demand data throughout supply chain networks, allowing for the extraction of forecasting rules. These methods need sophisticated algorithms coded into computers and are known to be computationally demanding [10], [11].

When dealing with unpredictable demand and supply, Fuzzy Logic becomes a lifesaver. In addition to the standard quantitative data, it enables firms to factor in qualitative indications like market mood, expert views, or subjective risk evaluations [12]. By considering demand volatility, lead time variations, and supply disruptions, Fuzzy Logic models can dynamically adjust inventory policies to ensure optimal inventory levels and minimize the two worst-case scenarios: stockouts and excess inventory. Fuzzy Logic might be helpful when making supplier selections based on subjective, non-quantifiable factors, such as gut emotions. Subjective evaluations, qualitative elements, and various criteria, including quality, price, lead time, and location, are standard supplier selection procedures [8], [13]. Using Fuzzy Logic in supplier selection allows for a more thorough and nuanced conclusion by enabling decision-makers to include their experience and subjective preferences in the assessment process. This combination of mathematical and human decision-making procedures explains the intricate character of the SC. Accurate demand projections, when used by a forecasting manager, maybe a potent instrument for creating a comprehensive demand picture [8], [14]. Demand and sales forecasting are two areas of predictive analytics that impact every company and are used to eliminate supply chain inefficiencies [15]. Customer happiness and inventory stockout are directly affected by a reliable and effective model for demand, supply, and price forecasting. For SCM systems to work correctly, businesses must enhance their demand forecasting models to meet client demands better [16]. Companies might get a deeper insight into their customers' wants and requirements, tailor their services to meet those demands, increase revenue and profit, and break into new markets if they advance the FL-BDDF framework.

SCM relies on accurate demand forecasts to help businesses maximize inventory optimization, minimize costs, and increase customer satisfaction. The problems contemporary SC present are typically difficult for

conventional demand forecasting methodologies to handle because of these systems' growing complexity, volatility, and unpredictability. To account for the dynamic nature of demand due to consumer behaviour, economic changes, and outside disturbances, these techniques depend too on past data and make assumptions about static patterns. By using various real-time data sources, including transaction records, social media, and Internet of Things (IoT) devices, Big Data presents unparalleled prospects to improve demand forecasting. There is potential, but current methods aren't up to processing the ambiguity and uncertainty of such large datasets. Little is known about the potential of combining BDA with Fuzzy Logic, which is well-known for its capacity to describe imprecision and uncertainty to improve demand forecasting. To fill this need, demand forecasting models must be enhanced by using innovative, integrated frameworks that combine BDA with Fuzzy Logic, allowing for more accuracy and flexibility. The proposed FL-BDDF framework hopes to overcome these obstacles and provide more accurate and context-aware demand forecasts by combining uncertainty modeling with real-time data processing. By filling this crucial need, the FL-BDDF framework aims to reform demand forecasting methods and improve supply chain decision-making in unpredictable and ever-changing environments.

The main contributions of the study are:

I. This article shows several applications of a demand forecast in supply-chain management in a business with sales executives and managers of promotion, product planning, financing, and product operations that manage the process.

II. To address demand and supply forecasting issues, this article lays out a data-driven approach involving operational analysis based on Big Data.

III. Using Fuzzy Logic models in training data allows for capturing demand fluctuation and uncertainty. It may also aid businesses in considering qualitative indications like expert views, market mood, or subjective risk evaluations.

IV. Businesses may make better use of the proposed FL-BDDF framework for demand forecasting with enhanced forecasting. It allows them to improve their decision-making in several areas, including product seasonality, customer satisfaction, reduced costs, and complexity.

Here is the structure of the part in the study paper: Section 2 research on demand forecasting is shown. Section 3 explains the FL-BDDF. Section 4 of the experiment is designated for the results, analysis, and comparisons to earlier processes. The paper provides an overview of the findings in Section 5.

2 | Related Survey

The article presented a Key Performance Indicator (KPI) in [17] for demand forecasting, leading to more cost-effective inventory management. Additionally, the researchers provide a fresh method for calculating the optimal safety stock quantity. This method considers the dependability of logistic network supplies and seasonality indicators in demand history. By analyzing real-world data, we demonstrate how the suggested strategy may enhance forecasting efficiency and safety stock levels while decreasing the likelihood of stockouts and excess inventory.

The models used in the research [18] include seasonal ARIMA, ARIMA with Fourier terms, TBATS, and ETS, which stands for trigonometric exponential smoothing state space model with box-cox transformations, Trend, ARMA errors, and seasonal elements. Despite being just as effective, the popular machine learning models are much more difficult to understand; these models are offered as an alternative. The chosen approaches were shown via a case study. After comparing the data, the optimal strategy was determined; it should be noted that all approaches might enhance supply chain demand forecasting.

Using Long-Term Memory Networks (LSTMs) as its foundation, the article suggests a deep learning method for demand forecasting [19]. Compared with other well-known time series forecasting approaches based on statistical and ML techniques, the suggested model has demonstrated superiority in capturing the non-linear characteristics included in the historical sales data of a drug manufacturing firm in Morocco. With an RMSE

of 4487.32 and a SMAPE of 0.026, the suggested technique outperformed the other models in comparing test outcomes.

The paper [20] explores machine learning algorithms for demand forecasting in SCM, focusing on long-term (4-5 years) and short-term (3-5 months) situations. Improving prediction accuracy is the main objective via feature selection algorithms and other deep learning and machine learning methodologies. Improving predicting skills might be one way this study's findings help decision-makers and practitioners take charge. The supply chain plan is guaranteed to be more complete and robust by including both projection periods.

In [21], a single-case explanatory technique was used in the investigation. The research determines ML methods that can be utilized for demand forecasting and evaluates how well ML can predict outcomes in the pharmaceutical SC. The study's findings demonstrated that an 80% accuracy level for training data partitioning was optimal, with random forest and simple tree algorithms surpassing others regarding demand forecasting accuracy. Accuracy gains in demand forecasting were between 10% and 41%.

The article suggests incorporating a mixed method of supervised learning and knowledge management processes for prediction into the supply chain's demand forecasting process [22]. It uses several data sources to enhance the process of explicit knowledge acquisition, optimize demand forecasting efficiency, and compare the found efficiency outcomes. Accordingly, KM practices are the most significant elements impacting supply chain demand forecasting, according to the research. A confusion matrix is constructed using the classifiers' accuracy and Kappa values, and their performance is evaluated in this way.

Nozari and Edalatpanah [23] suggested intelligent systems risk management in IoT-based SC. This research uses a non-linear fuzzy technique to rank the risks of deploying smart technologies in IoT SC . For sustainable and efficient growth, it is crucial to pay close attention to the risks stemming from a lack of knowledge and the neglect of technological infrastructure, one of the most significant risk factors in smart food chains.

Sıcakyuz [24] proposed the bibliometric analysis of Data Envelopment Analysis (DEA) in SCM. The study delves into the study trends around DEA in SCM, utilizing data collected from the VOSviewer and Web of Science (WoS) database software to map out the articles accurately. This bibliometric analysis takes 352 scholarly articles from prestigious journals and synthesizes their uses of DEA in SCM to comprehensively evaluate DEA in the discipline. Publication year, author(s), field(s), journal(s), and study topic are some of the ways the publications are categorized. The results of this study demonstrate that DEA has great promise as an appropriate assessment tool for future research on sustainability issues in SCM.

Nosratian and Taghavi Fard [25] recommended DEA and knowledge management to SCM. This article will assess how sharing information affects the effectiveness of the supply chain. Here, the cross-efficiency technique describes and scores seventeen distinct information-sharing situations. Lastly, results for several cases simulated in rockwell software arena V5 are shown. The findings demonstrate the validity and efficiency of the suggested model, making it suitable for use in real-world scenarios.

Edalatpanah et al. [26] discussed the two-channel pricing decisions in a multi-objective closed-loop supply chain network under uncertainty considering reliability. Uncertainty makes product price a critical node in supply chain networks since it affects every decision along the supply chain. An obvious consequence of changing product prices and consumer demand is its ripple impact on supply, distribution, and manufacturing. This article explores modelling a two-objective issue with green product strategies and pricing in the supply chain with non-deterministic maintenance costs, considering the role of pricing in the closed-loop supply chain. Optimal placement, routing, allocation, and inventory management are critical to maximizing supply chain network profitability and dependability.

Bahrampour et al. [27] deliberated the scenario-based fuzzy model for sustainable closedloop supply chain network. Along with the MOPSO and NSGA-II algorithms, a novel hybrid metaheuristic algorithm was suggested, drawing from the unique characteristics of both the genetic and grey wolf algorithms. They were assessed using MID, DM, and SM criteria after their parameters were tuned using the Taguchi technique, and

their performance was tested in problems of varying dimensions. At the 5% confidence level, there was no statistically significant difference in the indexes' performance across the three methods.

Banihashemi et al. [28] examined the Fuzzy BWM Method for identifying Green Supply Chain Management (GSCM) in the Construction Industry. Using literature research and expert comments based on SCM, this article identifies the components and sub-components of GCSCM. Afterwards, the sub-components were differentiated concerning each component. The discovered components and sub-components were then weighted according to their relevance using the fuzzy Best-Worst Method (BWM) based on the views of five experts with relevant practical expertise.

Fasihi et al. [29] investigated the multi-criteria analysis techniques to assist decision-making in renewable energy SC. Research on quantitative decision-making for renewable energy SC is better understood because of this paper's study. The first step of the study is to look for published publications. Afterwards, only the most relevant ones are kept. Also included are areas where the literature is lacking in information. Researchers interested in this field might use the results as a reference.

Malekinejad et al. [30] presented a sustainable closed-loop supply chain for reducing electronic waste. The original requirement for their identification was ten years of relevant professional experience or at least one publication in an international peer-reviewed journal. Using the snowball sampling approach, these people were chosen. In the end, 72 experts were chosen using the snowball sampling method. To help Iran deal with its electronic waste issue, this paradigm was used to build future and backward scenarios. According to this research, there has to be an attempt to reduce costs via improved recycling techniques rather than just throwing away a lot of electronic garbage. Businesses may contribute to a more sustainable future by recovering valuable materials from electronic trash and building a closed-loop sustainable supply chain.

Masoomi et al. [31] introduced the Neutrosophic Enhanced Best Worst Method (NE-BWM) for performance indicators evaluation in the renewable energy SC. The results highlight the significance of effective communication and teamwork among RESC members. Information exchange is essential to enhance cooperation and coordination in the SC. One major drawback of this research is the reliance on experts' subjective opinions in demography. According to the NE-BWM findings, 90% of the weight should be attributed to the top 10 indicators. Assuming this to be true, the study's main usefulness lies in its all-encompassing framework for the contemporary RESC of developing economies.

Nafei et al. [32] suggested the neural network-driven TOPSIS with Neutrosophic Triplets for green supplier selection in sustainable manufacturing. This study is necessary because existing techniques fail to appropriately evaluate options under uncertainty in Multi-Attribute Decision-Making (MADM) situations, which are becoming more complicated. The originality comes from combining NTs with a machine-learning strategy, which makes MADM's architecture more adaptable and strong. An important part of sustainable SCM is green supplier selection, where the suggested strategy shines. The findings demonstrate that the smart TOPSIS approach enhances decision accuracy while decreasing computing complexity, positioning it as a practical tool with the potential for wider applications. It is possible to apply the suggested technique to real-world situations in other study areas, even if it primarily applies to green supplier selection management.

Keyser et al. [33] proposed the absorbing markov chain for accounts receivable. Using a case study approach, this article delves into what it takes for a lean manufacturing company to pay its customers on time for their account transactions. A discrete-time absorbing Markov chain model examines two competing absorption states paid in full and bad debt write-off and five transitory states' new transactions, one month late, two months overdue, three months overdue, and four months overdue. Using a first-order Markov chain, we may characterize the periods starting with the completion of a new transaction as transitory states in the collections process. Ordinarily, Markov chain computations are run to determine where accounts receivable collections are projected to be.

Lazarashouri and Najafi [34] recommended the simulation and fuzzy Multi-Criteria Decision-Making (MCDM) integration for enhancing emergency department efficiency. To optimize and critically evaluate the

decision-making processes intrinsic to EDs, this model was integrated with the Elimination and Choice Expressing Reality (ELECTRE) and Analytic Hierarchy Process (AHP) approach within a fuzzy framework. After implementing these approaches, patient flow and service quality were markedly improved, demonstrating the great promise of combining simulation with fuzzy MCDM for healthcare operational excellence. This research provides a flexible technique that might be used in many hospital settings, which could improve emergency department operations.

Wang [35] discussed the smart farming through IoT enabled tools. With IoT technology, farmers may increase their yield per manure unit applied while decreasing water waste and irrigating crops. In addition, using AI sensor technology on a global scale improves crop yields, soil tracking, pest management, growing conditions, data coordination for farmers, workload assistance, and the advancement of other agricultural jobs along the food supply chain.

Montazeri et al. [36] deliberated the robust-fuzzy-probabilistic optimization for a resilient, sustainable SC with inventory management. Results from using the baron technique and the invasive weed optimization algorithm to the calculations reveal that demand has grown in proportion to the network's uncertainty rate. As a result, there has been a rise in the cost of ordering and maintenance and shortfalls. Additionally, the seller's overall inventory management cost has increased, and a larger consumer demand has been projected as the model's stability coefficient has increased. However, the number of orders passed to the buyer has declined as resilience increases. In addition, the computational findings demonstrate that the invasive weed optimization method effectively resolves the robust and sustainable supply chain model in conjunction with the seller's inventory management strategy.

The two-stage supply chain in DEA-R with random data using the Centralized Allocation Resource (CRA) model was proposed by Mozaffari and Ostovan [37]. Using a two-stage linear programming technique, the CRA captures the projection of DMUs on the efficient frontier. The input and output vectors of each DMU in the DEA might reflect data that follows a specific distribution and is, therefore, possibly random due to their critical nature. Therefore, random data is a problem for many applicable investigations. In this study, we see how to project DMUs using a two-stage supply chain that uses random data and the CRA model that uses ratio data. Ultimately, sustainability considerations were applied to the supply chain of eleven Iranian Airlines using randomly selected data from 2011 to 2017.

Kumar et al. [38] offered a Big Data-driven model for demand-driven predicting with the effects of marketing-mix parameters. The precision of demand projections is the overarching goal of this article. The goal is to accomplish this by comparing the performance of a back-propagation neural network-based model trained with fuzzy inputs to benchmark forecasting approaches applied to time series data. This data set includes historical sales and demand data and information about advertising effectiveness, expenditure, promotions, and marketing events. Experimental results demonstrate that the suggested framework's strategy outperforms efficiency, optimality, and other statistical metrics, corroborated by the numerical analysis. Lastly, we provide some priceless insights for managers looking to enhance fuzzy neural networks' prediction accuracy, create product marketing strategies, and cover their ramifications in many domains.

Fu and Chien [39] suggested the data-driven intermittent demand forecast model to empower SC resilience. This project aims to create a UNISON data-driven analytics model that uses ML and a temporal aggregation technique to predict when components of intermittent electronics will be needed. This framework will help meet practical demands for better demand forecast performance. A prominent semiconductor distributor worldwide conducts an empirical investigation to validate the hypothesis. Compared to more traditional methods and current practices, the findings demonstrate the practical viability of the suggested methodology.

Bamel and Bamel [40] proposed the fuzzy Total Interpretive Structural Modelling (TISM) approach for BDA-based enablers of SC capabilities and firm competitiveness. Supply Chain Capabilities (SCCs) and company competitiveness may be enhanced with the use of BDA, which is the focus of this study. In addition to identifying enablers, this article analyzes their interactions to predict how strongly these enablers relate to

SCC and a company's competitiveness. According to the findings, SCC and company competitiveness are greatly improved by BDA-based enablers, such as BDA-compatible IT infrastructure, leadership buy-in, BDA-user skills, and BDA funding.

Kazancoglu et al. [41] recommended the fuzzy-based hybrid decision model for circularity in dairy SC. A hybrid decision framework was created using fuzzy ANP and fuzzy VIKOR to determine the relative importance of the obstacles and rank the solutions driven by Big Data. Policymakers and managers may utilize the proposed Big Data solutions to address challenges in achieving circularity within dairy SC.

Beinabadi et al. [42] introduced Sustainable SC decision-making in the automotive industry. An integrated data-driven method that is specifically designed to tackle these difficulties is presented in this paper. The author successfully forecast the quantity of demand for automobile parts by using state-of-the-art AI methods, such as convolutional and recurrent neural networks fine-tuned with the Moth-Flame Optimization (MFO) algorithm. Our model attains a remarkable accuracy rate of over 90% via empirical validation with Iranian car parts manufacturers. Afterwards, 0.75 efficiency points are obtained when DEA considers providers' social, economic, and environmental consequences in addition to demand quantities. The BWM is used to narrow supplier selection further. The top providers are identified with an average score of 0.8. Roßmann et al. [43] presented the BDA in SCM. The author used a Delphi poll to include expert evaluations of predictions up to 2035. To discover future scenarios that span the future of BDA in SCM, we employed fuzzy c-means clustering. Researchers concluded that BDA would lead to more accurate demand predictions, less need for safety stockpiling, and better supplier performance monitoring. Automatic SC procedures will largely replace the conventional SCM duties. So, as SCM moves away from its conventional function in businesses, trust, intuition, and strategic decision-making will play an ever larger role.

Ma et al. [44] discussed the BD-driven risk evaluation technique using ML for SC in airport economic promotion regions. Accurate risk assessment via data analysis is crucial to enhance the successful development management of these places. Accordingly, this article suggests a Big Data-driven evaluation methodology for supplier chains in airport economic development regions using the ensemble learning concept. Finally, the approach proposed in this study is evaluated by tests performed on synthetic data, demonstrating its efficiency and practicality.

Hsu et al. [45] deliberated the Big Data enablers to strengthen supply chain agility to mitigate the bullwhip effect. Using the biggest relay manufacturer in China as an example, this study proposes a MCDM integrated model and uses Big Data to find ways to make SC more agile and less susceptible to the bullwhip effect. This method can help businesses adapt electronic equipment more rapidly to new circumstances. Supply chain agility may be improved, and the bullwhip effect can be mitigated with the help of these BD enablers. Other manufacturing firms may use this framework as a reference for SCM, and electronic manufacturers can use it to create indicators of SC agility and BD enablers to reduce the bullwhip effect.

Talwar et al. [46] offered the Big Data in operations and SCM. The present study used Systematic Literature Reviews (SLR) to find current research patterns, extract important themes, and pinpoint areas that need further investigation. A total of 116 studies were retrieved and evaluated for this objective after passing through a rigorous search procedure. The Dimensions Avenues Benefit (DAB) model for Business Process Automation (BPA) adoption and potential research questions to support new studies in the field are the main products of this SLR, which has practical implications for managers across industries and verticals.

Dutta and Bose [47] discussed the managing a Big Data project in Ramco cements limited. The author aims to accomplish two things in this paper: first, to develop a new framework that can help organizations with Big Data project planning, conceptualization, and execution; and second, we want to validate this framework by observing a descriptive case study of an organization that has done just that. Analytics are becoming more popular in product development, operations, and logistics, but the industrial sector has been sluggish in utilizing them in making strategic decisions. The author looks at Ramco cements Limited's an Indian manufacturing business Big Data project, details the system they built, and highlights the advantages it brought about. Using the suggested framework as a prism, it examines the project's implementation process.

Kundu et al. [48] presented the Latent Semantic Analysis (LSA) for SCM. The research gains a scientific foundation from the LSA-based analysis, which aids in eliminating the subjectivity of collective judgment on the patterns. Using this method, a taxonomy of studies examining the effects of power on SC may be proposed. Each taxonomic class has a research deficit filled using the accepted systems methodology. Studying behavioural operations in the supply chain shows signs of a new trend. To consolidate the many advancements of this interdisciplinary field, scholars will benefit from understanding such a scholarly framework and future trends. Practitioners who consider behavioural factors while making decisions may find this review useful.

Demand forecasting becomes a high-dimensional challenge in increasingly complicated SC with many items, consumers, warehouses, and supply sites. Thus, the literature review provides an overview of the several data analytics-based modelling methods offered for SCM demand forecasting. Some advantages of using FL-BDDF in SCM include lower operating expenses, more agile SCs, and happier customers. ML approaches have been utilized to predict demand in SCs, considering pricing, market, competition, and consumer behaviour uncertainty to enhance the efficiency and profitability of SC management. Regarding demand forecasting in unpredictable and dynamic supply chain contexts, the suggested FL-BDDF framework is unique since it combines BDA with Fuzzy Logic. The FL-BDDF framework uses Fuzzy Logic to represent and handle uncertainty instead of the static patterns used by standard statistical models or machine learning-based techniques. This connection enables the framework to combine varied and frequently neglected real-time data sources, such as IoT feeds, social media trends, and transaction records.

Furthermore, to improve the accuracy and flexibility of forecasts, the framework incorporates a rule-based approach that is flexible enough to account for contextual elements such as market swings, external disturbances, and seasonality. The FL-BDDF can manage noisy, high-dimensional data seen in Big Data settings because of its emphasis on scalability. It also offers strong comparisons with older approaches to show how it is better at what it does. As a result of these novel features, the FL-BDDF framework is now considered a cutting-edge tool for SCM demand forecasting.

3 | Proposed Framework

Strategies at all levels of an organization are predicated on forecasts, making forecasting a crucial activity for every business. Market size, growing markets, new competitors, future trends, and consumer wants are all factors the marketing department considers when making forecasts. To allocate funds, the accounting team utilizes forecasts to evaluate past financial results and identify areas needing capital investment. The operations department decides production and inventory levels based on the demand estimate. To choose vendors and make purchases, sourcing activities need projections. An accurate prediction is the first step in creating long-term plans. Since demand forecasts impact the strategies of every firm in the supply chain, they are vital for the whole system. Without sharing information, businesses throughout the supply chain are more likely to make erroneous predictions based on data collected from the immediate buyer rather than the ultimate user. A phenomenon known as the bullwhip effect an increase in order volatility as they move through the supply chain occurs when demand estimates are not communicated. The impacts of bullwhip on the supply chain are far-reaching: higher inventory levels, less effective use of working capital, and wasted manufacturing capacity. The participants in the supply chain use a Collaborative Planning, Forecasting, and Replenishment (CPFR) strategy to get over these issues. CPFR allows businesses to collaborate on supply chain optimization projections and strategy by creating a consensus demand estimate.

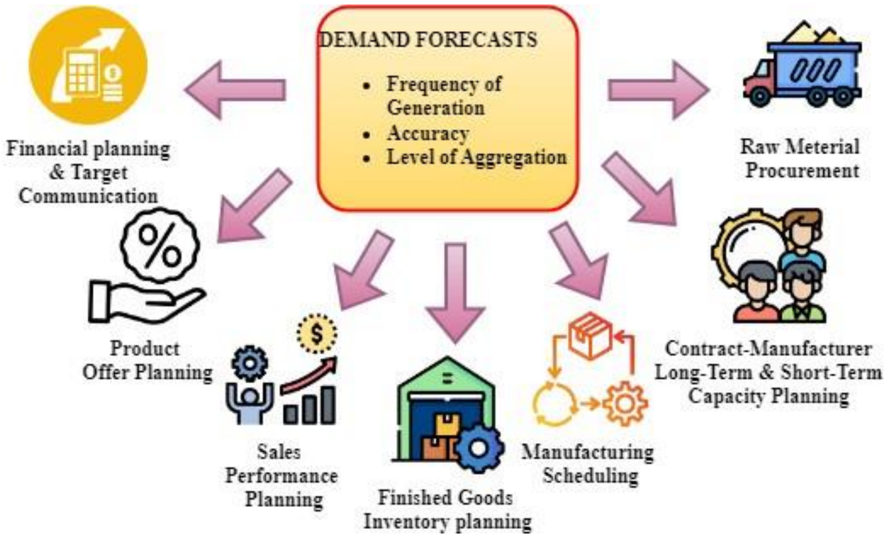

Fig. 1. Demand forecasting in supply chain management.

Identifying the decisions is a critical first step since every prediction supports decisions based on the forecast. Determining the quantity to manufacture, stock, or purchase is an example of such a choice. Everyone involved in a supply chain decision must understand how it relates to the prediction. A company's planning efforts throughout the supply chain should be based on its prediction. Just a few examples are planning for capacity, manufacturing, advertising, and buying. There has to be a connection between the HR department and the information system. The results of the planning process impact many different areas. Thus, all of those areas must be considered when making predictions. One typical but terrible situation is that a producer is in the dark about promotional efforts while a retailer uses them to inform their projections. Creates a new forecast for production planning using past orders as input. The result is that supply and demand are out of sync, leading to subpar client support. A company has to *Fig. 1* out which parts of the supply chain are used by which types of customers. Similarities in service needs, demand quantities, order frequency, demand volatility, seasonality, and other factors might help classify customers. In general, businesses may use segment-specific forecasting approaches. An accurate and streamlined forecasting method is made possible with a comprehensive grasp of the consumer categories. Before making a demand prediction, a company must determine what factors affect supply, demand, and product-related events. From a demand perspective, a business needs to know whether demand increases, decreases, or follows a seasonal trend. Data on demand sales must form the basis of these estimations. Understanding the key dimensions is the first step for a corporation in picking an acceptable forecasting approach. Location, categories of products, and categories of consumers are all examples of such dimensions. The business should know that demand varies in each dimension and will likely need separate predictions and methods. At this point, a company decides which forecasting approaches qualitative, time-series, causal, or simulation will work best for them. As shown before, a mixture of these approaches usually yields the best results. Businesses should set clear performance metrics to ensure the prediction is accurate and delivered on schedule. Decisions made by companies based on these predictions should have strong correlations with these metrics.

Demand forecasting plays a crucial role in SCM by predicting future customer demand, enabling companies to optimize their operations. Leveraging advanced technologies like Big Data and Fuzzy Logic can significantly enhance the accuracy and efficiency of demand forecasting.

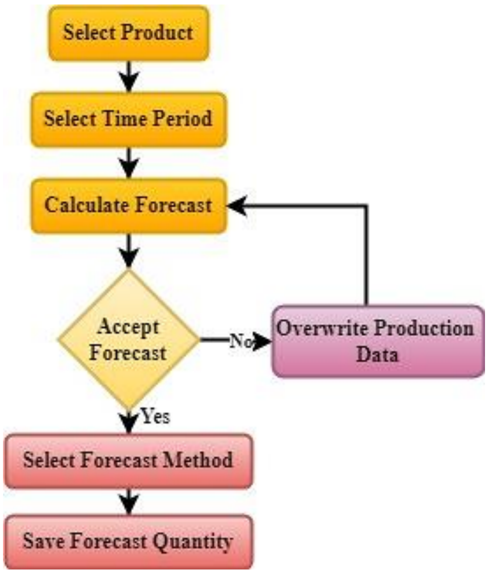

Fig. 2. Framework of demand forecasting process.

Forecasting is the process of predicting an upcoming occurrence. In the majority of businesses, the process of forecasting demand involves making gradual changes to the initial, naive estimates. Evidence of the process's complexity, unpredictability, and ambiguity may be seen in market returns and stockouts. Ensuring the generated forecasts are as near to the actual as feasible is of the highest significance because their accuracy affects the whole supply chain. Production targets are determined using this forecast in addition to fixed orders and sales rep requests. There is a shortage of comprehensive data about forecasting methodologies, which is likely because many companies fail to recognize the importance of demand forecasting in deciding the efficiency of their supply chain. So, developing methods and tools to make these critical decisions quickly and with minimum human intervention is necessary.

Fig. 2 provides a bird's-eye view of the demand forecasting process. A DSS may be defined as "a computer program intended to assist in identifying and assessing alternate possibilities of action." Decision Support Systems (DSSs) compile data from a business's regular, high-volume transactions, analyze it with advanced statistical methods to pull out pertinent information, and finally, narrow down the choices that exist by applying decision-theory depending rules. Its stated goal is to facilitate "what if" analysis rather than to supplant a manager's discretion. DSS aid in decision-making but do not take the role of human managers or employees. The authors conceptualized and built the system. The authors of this study believe that developing software is an original scientific advancement in demand forecasting and scheduling.

This is because it is preferable to have software that can simulate many what-if scenarios and show the consequences in a realistic planning environment. Many different industries have recently seen the publication of advanced demand planning systems for demand planning. Some individuals' strategies include the use of simulations and modelling tools. Small and medium-sized businesses, on the other hand, are unable to afford these complex modelling approaches since their licensing charges are much higher than the industry standard.

3.1 | Big Data in Demand Forecasting

3.1.1 | The process of collecting and combining data

I. Research is the process of gathering information from various sources, including but not limited to financial transactions, social media, market movements, weather, and economic indicators.

II. Integration refers to combining all data from different sources, consisting of structured and unstructured information, into a single centralized system to conduct comprehensive analysis.

3.1.2 | Data analysis

I. Descriptive analytics: a summary of historical data is being performed to identify patterns and trends.

II. Predictive analytics: based on historical data and trends that have been identified, statistical models and machine learning algorithms are used to make predictions about future demand.

3.1.3 | Realtime processing

I. Stream processing: this involves conducting real-time data analysis to adjust demand forecasts immediately.

II. Adaptability: the process of continuously updating forecasts based on new data to represent the most recent market conditions accurately.

3.1.4 | Enhanced accuracy

I. Granular insights: improvements in forecast accuracy can be achieved by providing detailed insights at multiple levels, including product, store, and regional levels.

II. Volume and velocity: managing large amounts of data at a high rate of speed to capture the ever-changing nature of customer service.

4 | Fuzzy Logic in Demand Forecasting

4.1 | Handling Uncertainty

I. Fuzzification: the transformation of crisp inputs, which are exact data, into fuzzy sets is done to address the issue of uncertainty and imprecision in demand forecasting.

II. Linguistic variables: to make the model more understandable, it is possible to explain predicted variables using language phrases such as high demand and low demand.

4.2 | Rule-Based Systems

I. IF-THEN rules: the process of developing a set of rules designed to simulate human thinking, such as "if sales are high and market sentiment is positive, then demand will increase."

II. Expert knowledge: enhancing forecasts' reliability by incorporating experts' knowledge and experience into the rule-based system.

4.3 | Aggregation and Defuzzification

I. Aggregation: combining some fuzzy rules to generate an all-encompassing forecast.

II. Defuzzification: the fuzzy output is converted to a numerical value to provide an accurate demand forecast.

5 | Integration of Big Data and Fuzzy Logic

5.1 | Data-Driven Fuzzy Logic Models

I. Learning from data: using BDA, patterns and trends are identified as the basis for developing fuzzy rules.

II. Dynamic updates: making continuous improvements to Fuzzy Logic models based on real-time data to improve the accuracy of forecasts.

5.2 | Enhanced Decision Making

I. Scenario analysis: to evaluate the influence of various factors on supply chain operations, simulations of different demand scenarios are being carried out.

II. Proactive planning: using demand forecasts to inform supply chain strategy adjustments makes proactive decision-making possible.

6 | Benefits of Supply Chain Management

I. Improved forecast accuracy: raising the accuracy of demand projections while lowering the risk of stockouts and excess inventory.

II. Cost reduction: minimizing the costs associated with holding inventory and optimizing production and procurement processes.

III. Enhanced responsiveness: to react more quickly to shifts in the market, supply chain operations should be made more agile.

IV. Strategic planning: providing dependable demand projections to support long-term strategic planning.

Regarding SCM, including Big Data and Fuzzy Logic in demand forecasting provides a robust and data-driven strategy that enhances accuracy and responsiveness regarding the forecasting process. By capitalizing on the advantages offered by both technologies, businesses can improve their operational efficiency and better satisfy the requirements of their customers, eventually earning a competitive advantage in the market.

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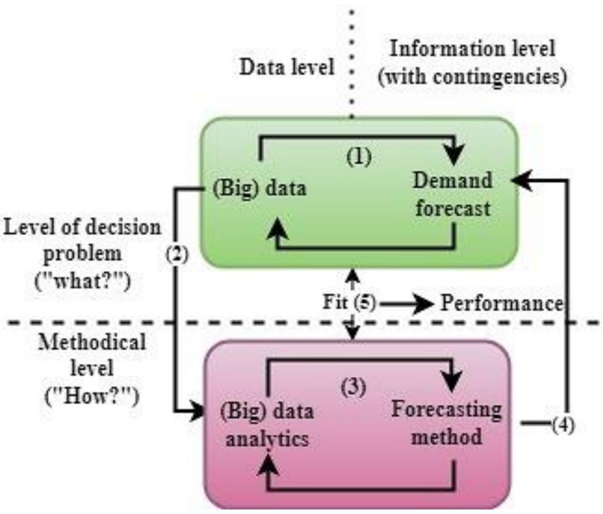

Fig. 3. BD-based demand forecasting.

A technique known as the two-sided systems approach is used to produce an explanatory instantiation. The objective of enhancing demand forecasting techniques via BD is to provide a theoretical basis for using BD. This section will talk about the most significant steps for connecting the components. The entities of interest are connected via decision cycles, demonstrating a streamlined sequence of activities and corresponding requirements between these stages ("interplay" in the recommended information systems design process). Since decision-making and the factors influencing demand predictions are inherently uncertain, we include a contingency framework in every process phase. The organizational structure determines the effectiveness and efficiency of management control systems; as a result, the arrangement of the data with technology and the environment reveals significant principles and restrictions for using the system in the future. Although the phrases "data" and "information" are sometimes used interchangeably, there is a distinction between the two that primarily relates to the function that each term serves. A collection of values that may be described as qualitative and quantitative variables is used to collect and assess the considered data. The processing and

bundling of data within a specific context (for example, a retail supply chain) enables information generation by providing the decision-maker with meaning and structure. This is accomplished via the provision of a specific context. The only way for businesses to get data that has been refined into something that can be used for decision-making is by taking this approach.

Furthermore, the framework differentiates between the data and information levels based on contingencies. This differentiation is possible inside the framework. One must first determine the decision issue and its strategy to solve difficulties. It is clear from *Fig. 3* that the demand forecast is the first step of the data-decision cycle, which is also the point at which the conceptual framework is initiated. While transmitting the "value chain of Big Data" again, further items are added counterclockwise to complete the iterative loop. This study [49] examined 2010–2012 data from 45 Walmart stores nationally. External statistics like the CPI, unemployment rate, and gasoline price index for each store's location might help us form conclusions.

7 | Interconnections

The breadth and the amount of interaction of decision-making issues, often known as demand predictions, are characteristics of these challenges. Different needs and input variables are used depending on whether the emphasis is on choices that are in the long term (such as the placement of sites or the method of transportation) or decisions that are in the short term (such as category management or routing) (see *Fig. 3*). The almost infinite number of operations throughout the supply chain generates various data types. Consequently, particular internal and external data sources must be tapped ((i) Data Sources) to estimate demand, depending on the forecast accurately. When making choices for a company, it is necessary to measure and evaluate the various risk components carefully (see *Fig. 3* for more information).

Consequently, methodological approaches to forecasting serve as a foundation for risk reduction within the decision-making process. Consequently, the selection of the appropriate procedure is of the utmost importance. When there is a chance that historical data will be insufficient or unavailable, the starting situation largely determines the approach chosen, and vice versa. In addition to that, the data that was tapped has to be merged ((ii) integrate data). Every choice has an element of uncertainty that cannot be assessed or minimized using the often-used statistical forecasting tools. The condition of uncertainty may be transformed into a state of risk if the person making the choice can recognize the many possibilities that might occur and then proceed to evaluate and assign probability to each of those scenarios. As a result of the fact that its many applications take into consideration not only several variables but also a significant amount of data in terms of volume, velocity, and diversity, BDA has these capabilities. To enhance demand forecasting, it is necessary to guarantee the interaction and compatibility between the forecasting technique and BDA applications (see *Fig. 2* for more information). A computational shift is produced as a result of this match, which enhances demand forecasting capabilities and broadens its scope. At this stage, the actual data analysis is carried out ((iii) Analyze Data). Since the information that is currently accessible is often faulty and partial, BDA frequently calls for new data to adapt to the decision issue. The iteration inside the loop will continue until the model-driven decision support seems to be enough and the intended result is accomplished ((iv) Actionable Insights). Even when using a Fuzzy algorithm or a one-size-fits-all approach to demand forecasting, it is impossible to ignore the relative influence of many demand variables, such as the firm's size, the sector in which it operates, and the product line. The goods depend on the ability to respond to changing market circumstances and the behaviour of consumers. To enhance performance (for example, utilizing enhanced business management), it is necessary to achieve alignment in internal consistency, congruency, or fit between various dimensions (see *Fig. 3* for more explanation). Not only does an efficient organization have a good fit with its surroundings, but it also has a good fit between its subsystems and the technology components that make up its composition. So, one of the leading performance goals of BDA applications should be to get better predictions by correctly interacting with specific forecasting methods.

The FL-BDDF framework handles supply chain demand forecasting uncertainty and variability using Fuzzy Logic to represent imprecision and variability. BDA meanwhile, picks up on trend dynamics and contextual

aspects. To account for unpredictable inputs like changing sales, seasonal changes, and outside disturbances, Fuzzy Logic employs membership functions to describe these factors as linguistic variables (e.g., "low demand," "moderate demand"). The framework can infer demand patterns even in vague situations thanks to a rule-based system that handles these data. At the same time, BDA finds new patterns and hidden connections in massive, heterogeneous datasets that are processed in real time. More accurate, context-aware, and resilient demand predictions in dynamic supply chain settings are the outcome of integrating these methodologies, which combine the predictive power of Big Data with the flexibility of Fuzzy Logic. This integration guarantees robust management of unpredictability.

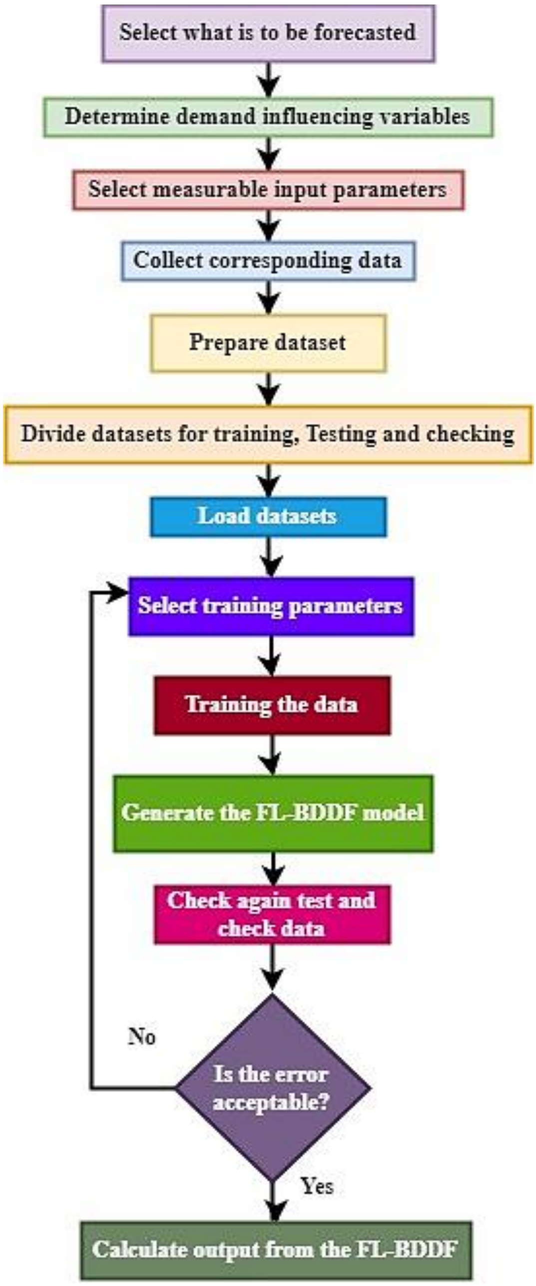

Fig. 4. Demand forecasting processes with Fuzzy Logic.

The demand forecasting process is another essential task that the warehouse management team does, provided all purchase orders are verified with appropriate inventory. The receiving processes are more straightforward and less complex than the picking process, and the offered solution, when combined with Fuzzy Logic methodology, provides the best forecasting strategy for increasing operational efficiency. Among the advantages of the Fuzzy Logic model over competing methods is its ease of understanding by the end

user. The Fuzzy Logic model employs an analytical procedure, fuzzy values, and linguistically imprecise terms. The model's remarkable simplicity of understanding aids in the practical evaluation of non-numerical or partial input data, which is helpful for qualitative aspects like configuration ability. Its second benefit is the capacity to add end-user domain knowledge or business logic into measurement, which is achieved by improving or adapting its fuzzy systems. *Fig. 4* shows a process flow diagram for demand forecasting using Fuzzy Logic. Upon receipt of products from manufacturing, the data gathering module utilizes IoT technologies to record information about the items, such as the client's details, quantity, and location. Ideally, this data would allow us to determine the best strategy for reducing computational costs. This module applies Fuzzy Logic theory to the problem of customer demands to find the optimal method for improving the efficiency of order choosing. By modelling uncertainty and imprecision in real-time Big Data inputs using a Mamdani-type Fuzzy Inference System (FIS), the FL-BDDF framework integrates Fuzzy Logic into the demand forecasting process. It all starts with fuzzifying these inputs into language categories (such as "low," "moderate," and "high") using membership functions. This is done for inputs like sales patterns, economic indicators, and seasonal changes. An if-then rule set grounded on domain knowledge for non-linear and ambiguous situations captures the relationships between these variables. For example, a rule may propose: "If demand is high and inventory is low, forecasted demand is very high." After applying fuzzy operators to these rules, the Mamdani FIS produces fuzzy outputs that are further defuzzified into precise numerical values using the centroid approach. Improving the accuracy and adaptability of demand projections in ever-changing supply chain contexts, this integration enables the framework to interpret complex and ambiguous data successfully.

Regarding the Fuzzy Logic engine, the initial phase is called "fuzzification." Following data collection, the input data are transformed into a fuzzy set, and the membership function is primarily responsible for determining the characteristic. The *Eq. (1)* for this is as follows:

$$N_{gd} = \left(V\backslash_{\mu jl} \in [0,1]; \sum_{j=1}^{d} \mu jl = 1; 0 < \sum_{l=1}^{o} \mu jl < o \right). \qquad (1)$$

In this case, j is between 1 and d while l is between 1 ando. The fuzzy inference engine formulates rule blocks and composes rules as part of the inference process, which begins with transferring the input fuzzy set into the engine. Furious logic culminates in defuzzification. Results from defuzzification are computed using Graded Mean Integration Representation (GMIR). The contents of the GMIR may be found here: Assume that M^{-1} and S^{-1} are the inverse functions of functions M and S, respectively. Assume further that the graded mean h-level value of the generalized fuzzy number $B = (d, b, c, e; x)_{LR}$isi$[M^{-1}(i) + S^{-1}(i)/2)$. Then, using the grading mean's fundamental value as a basis, one may describe the hybrid fuzzy number i -levels as *Eq. (2).*

$$Q(B) = \frac{\int_0^x i(\frac{M^{-1}(i) + S^{-1}(i)}{2})ei}{\int_0^x iei}, \qquad (2)$$

where i is between 0 and$x$, $0 < x \leq 1$, clear metrics may be produced to assess the technique for the selector's action in the selection process. When there is a lack of translational value in the historical demand data to establish the required forecast value, fuzzy models with time series work well with dynamic systems like Scs. Here, the paper developed two fuzzy time series, one of which is first-order time-variant and the other of which is first-order time-invariant, using Fuzzy Logic to predict issues.

This article uses Fuzzy forecasting methods to predict consumer demands for seasonable products. Here is a brief overview of the model:

I. The first step is to find the lowest and most significant increases (E_{min}andE_{max}, respectively) and the variance between two sets of continuous historical data for improving supply chain forecasting demands.

II. The following *Eq. (3)*, which makes use of E_{min}andE_{max}, will be used to define the universe discourse, V_e.

$$V_e = E_{min} - E_1, E_{max} + E_2, \tag{3}$$

where *Eq. (3)* shows the positive values of $E_1$and $E_2$are appropriate for dividing V_e into equal lengths.

The next step is to fuzzify the variation data and construct fuzzy sets on V_e (i.e., define fuzzy time series, or $(G(U))$). The cost reduction function in demand forecasting$G(U)$ is defined in *Eq. (4)*.

$$G(U) = {}^{Q_{A1}}/_{v_1} + {}^{Q_{A2}}/_{v_2} + \cdots + {}^{Q_{An}}/_{v_n}, \tag{4}$$

where each membership Q_{Aj} is between $0 \leq Q_{Aj} \leq 1$. This allows us to express the fuzzy sets $BofV$ as *Eq. (5)*.

$$B = \left\{{}^{Q_{A1}}/_{v_1} + {}^{Q_{A2}}/_{v_2} + \cdots + {}^{Q_{An}}/_{v_n}\right\}. \tag{5}$$

A variation's fuzzy classification is based on the user interface v_jThat it best fits.

The last step in using the calculated variation to forecast future value based on the relation of the change value gained from the relation matrix is to defuzzify it. The matrices for operations and criteria $(P^x(u), A(u))$ will serve as guidelines for this variant. Here, we will find out that the windows foundation is x. This variable indicates the number of periods of variations to be considered for forecasting. The following is defined during the $u, P^x(u), A(u) and S(u)$ period can be represented as *Eqs. (6), (7), (8.a)*, and *(8.b)*.

$$A(u) = G(u-1) = [A_1, A_2, A_3, \dots \dots, A_o]. \tag{6}$$

$$P^x(u) = \begin{bmatrix} G(u-2) \\ G(u-3) \\ . \\ . \\ G(u-x-1) \end{bmatrix} = \begin{bmatrix} P_{11}P_{12} \dots P_{1n} \\ P_{21}P_{22} \dots P_{2n} \\ \dots \\ \dots \\ P_{x1}P_{x2} \dots P_{xn} \end{bmatrix}. \tag{7}$$

$$S(u) = \begin{bmatrix} P_{11}yA1 \ P_{12}yA_{11} \dots P_{1n}yA_n \\ P_{11}yA1 \ P_{12}yA_{11} \dots P_{1n}yA_n \\ \dots . \\ \dots \\ P_{11}yA1 \ P_{12}yA_{11} \dots P_{1n}yA_n \end{bmatrix}. \tag{8.a}$$

$$S(u) = \begin{bmatrix} S_{11}S_{12} \dots . S_{1n} \\ S_{21}S_{22} \dots . S_{2n} \\ \dots \\ \dots \\ S_{x1}S_{x2} \dots . S_{xn} \end{bmatrix}, \tag{8.b}$$

where $1 \leq k \leq nandS_{jk}yA_k, 1 \leq j \leq x$. Then, the estimated variation will be determined based on equality.

$$G(U) = {}^{Q_{A1}}/_{v_1} + {}^{Q_{A2}}/_{v_2} + \cdots + {}^{Q_{An}}/_{v_n}. \tag{9}$$

The FLs forecasting technique is completed by $s_k = Max(S_{jk}); j = 1,2, \dots \dots, xandk = 1,2, \dots ., n$, which is the forecast value for the period u, which is obtained by defuzzifying $G(u)$ and adding this value to the actual data of the period $u - 1$ in the above *Eq. (9)*.

To address the inherent imprecision and uncertainty in supply chain demand forecasting, the FL-BDDF framework employs generalized fuzzy numbers. This is especially useful when dealing with complex, dynamic, and noisy data. In generalized fuzzy numbers, the "x" is a parameter that lets you change the form of the fuzzy set on the fly. This way, the model can account for more data variances and possibilities. Due to the inherent fuzziness of real-world data, conventional fuzzy sets with rigid membership functions may not adequately represent it. Forecasting models should be more accurate with the help of generalized fuzzy numbers, which, in theory, provide a more complex picture of uncertainty than traditional fuzzy numbers. To better account for the variety of demand patterns affected by promotions, weather, and customer behaviour, generalized fuzzy numbers may be used, for example, in demand forecasts for a retail business during the festival season. Predictions that are more flexible and sensitive to context are the outcome.

The proposed FL-BDDF framework combines statistical analysis, fuzzy inference modelling, and data preparation to merge BDA with Fuzzy Logic. Before Big Data can be used, it must undergo preprocessing to guarantee data quality and handle high-dimensional datasets.

This includes methods like normalization, feature extraction, and dimensionality reduction, such as Principal Component Analysis (PCA). These cleaned-up inputs are further examined using statistical approaches or machine learning algorithms, such as clustering or regression, to find trends and patterns. In a Mamdani-type FIS, the processed data is fed into a rule-based framework that converts associations between variables into fuzzy rules, and membership functions reflect uncertainty. The approach integrates fuzzy inference findings and the crisp outputs from BDA using data fusion methods like weighted aggregation and multivariate optimization. Improved accuracy and flexibility in demand forecasting are outcomes of this hybrid model's successful capture of supply chain data's dynamic and unpredictable character.

This article discusses demand forecasting for the SCM section. The primary emphasis is placed on the production systems that are made-to-stock and make use of open-source technologies that are publicly accessible. This study concludes that it effectively integrated two domains: the analytical domain and the system development domain. As a result, incorporating the proposed FL-BDDF framework into the system has resulted in the DSS included in this study being placed in competition with other forecasting systems.

8 | Results and Discussions

These contextual investigative activities are powered by applying demand forming, tracking, and precise demand forecasting to SCM, Big Data, and the Fuzzy Logic model. According to the study's results, the suggested hybrid model significantly enhances predicting accuracy compared to other standalone models. With the suggested FL-BDDF's assistance, industry decision-makers can make more precise predictions, facilitating the development of seasonal items, decreasing supply chain costs, increasing consumer satisfaction, and simplifying operations. Supply chain efficiency may be enhanced with the help of an accurate demand forecasting system, which can do away with the bullwhip effect and ensure correct inventory management.

8.1 | Dataset Description

Sales projections are vital to any company's strategic plan. We'll examine the internal and external factors that may affect one of the major US corporations' weekly sales. This module includes time series analysis, data analysis, store performance identification, and multiple linear regression sales forecasting. This study [49] examined 2010–2012 data from 45 Walmart stores nationally. External statistics like the CPI, unemployment rate, and gasoline price index for each store's location might help us form conclusions.

8.2 | Accuracy

The accuracy of forecasts may be evaluated using *Eq. (10)* of Mean Absolute Percentage Error (MAPE). Prediction error types may be better anticipated by keeping tabs on the distribution of prediction mistakes. The MAPE is a statistical indicator that averages the percentage of forecast mistakes. Products with high-volume demand are often simpler to forecast than those with low-volume demand. Predicting product demand across several locations is also more straightforward than trying to do so at each location. As a measure of how well demand predictions match actual demand, forecast accuracy is a crucial KPI shown in *Fig. 5*. It is often reported as a percentage and is determined by comparing the actual demand with the predicted inaccuracy. Foreseeing demand for the near future is much easier than for the far future. The quantity of valuable data at the disposal is another factor that determines the accuracy of the achievable prediction.

$$\mathrm{MAPE} = \frac{1}{x}\sum_{t=1}^{x}\left|\frac{s_t}{j_t} \times 100. \qquad (10)$$

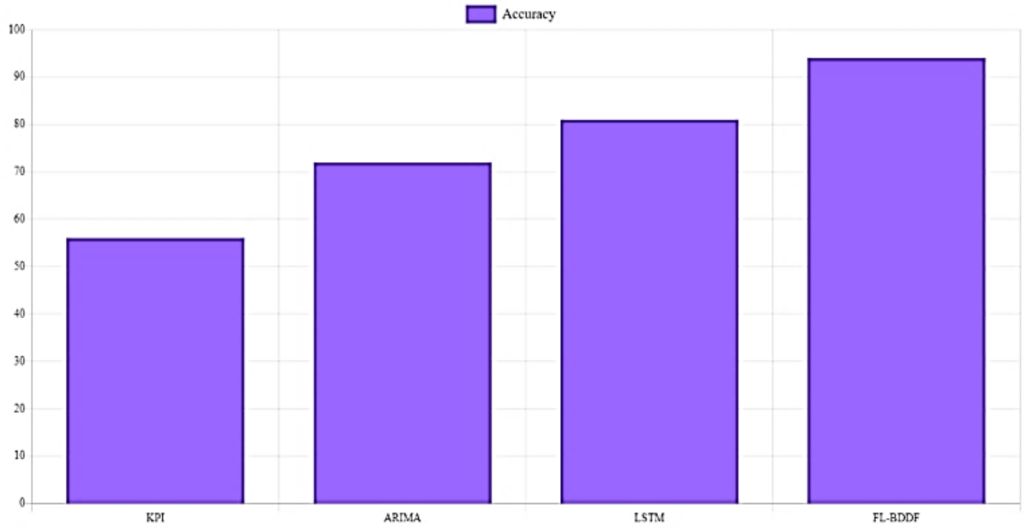

Fig. 5. Accuracy.

8.4 | Improving Supply Chain Forecasting

Fig. 6 shows the seasonality, new product launches, promotions, and causative variables (such as weather and social media) may make demand planning much more complicated than it already is, adding to the already great difficulty in predicting and keeping up with consumers' ever-changing demands (refer *Eq. (3)*). Machines are well-suited to handle parts of supply chain planning that need analysis and repeated computations because they are more efficient and precise than people. Machine learning is the ideal companion to human planners, as it can filter through masses of data for trends (such as buying habits and seasonality) and improve its accuracy with each passing day. Retailers and businesses with an in-depth understanding of their clientele will find this particularly useful.

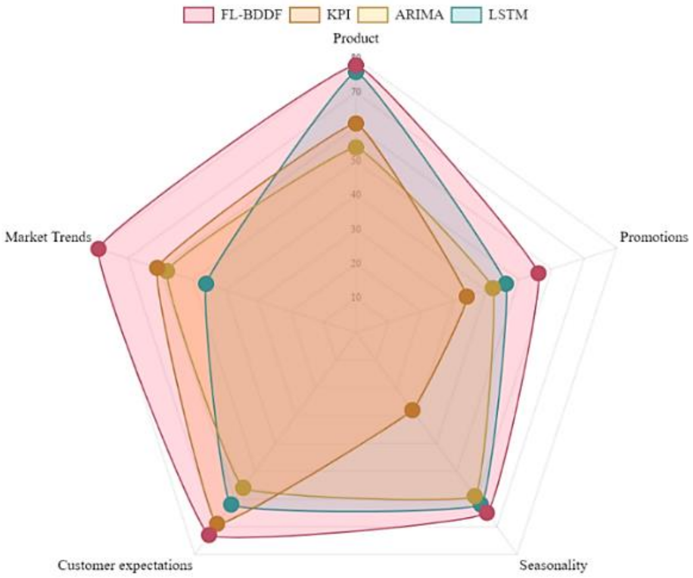

Fig. 6. Improving supply chain forecasting.

8.5 | Customer Satisfaction on Demand

Customers expect to find the goods in stock when they purchase. An essential part of the customer experience, satisfying demand, has a direct negative effect on your brand value if you ignore it. When

considering an omnichannel purchasing experience, fulfilling client demand becomes even more critical. To maximize sales and meet client demand, it's not enough to have the proper quantity of things; they also need to be in the right place. By putting the correct product in the right place, adequate inventory allocation makes a customer-centric strategy that optimizes revenue possible. Customer satisfaction and cost savings may be achieved by meeting their expectations about product availability and delivery dates, which is crucial in today's competitive industry (refer to *Fig. 7*). Take statistics from the supply chain as an example. It shows that when organizations invest in the customer experience, 57% of them anticipate cost optimization.

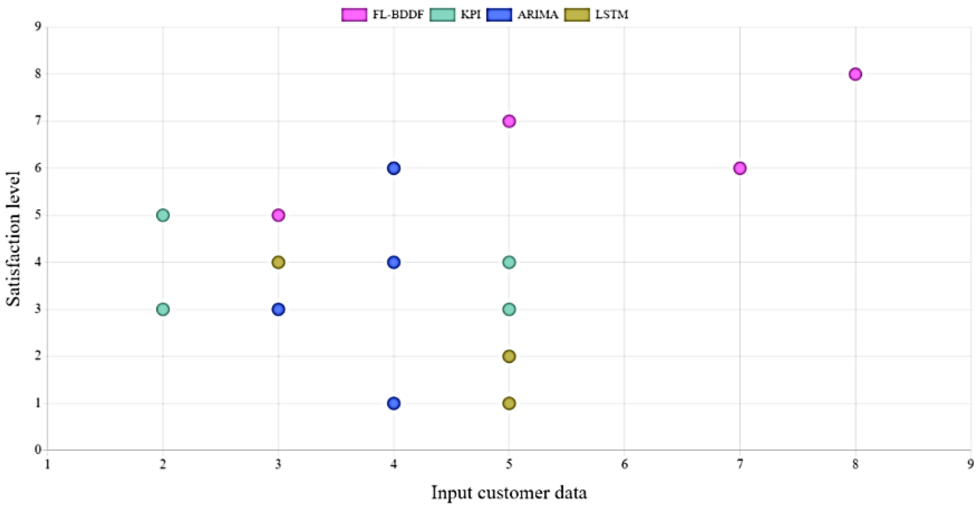

Fig. 7. Customer satisfaction on demand.

8.6 | Reduced Costs

Retailers use merge orders and improvements to lead time and zoning to lower distribution costs by using *Eq. (4)*. While implementing strategies like pricing, Vendor-Managed Inventory (VMI), and market segmentation, hypermarket merchants must consider the supply chain's capabilities and limitations. Managers in the retail industry must deal with massive amounts of uncertainty every day, leading them to fail at accuracy and incur significant supply chain costs (see *Fig. 8*). Research suggests using the right forecasting approach to get accurate results and make things easier for organizations.

A comprehensive picture of the organization is necessary to determine the enhanced value provided via cost reduction and price drop for the end consumer. When strategic forecasting policy was being implemented, there were instances where the forecasting produced favourable outcomes despite the high levels of uncertainty and little quantitative data. There is constant uncertainty in the face of threats to existence, such as shifting demographics, disruptive technology, novel business models, and other such issues. Managers thus look both internally and outside to find the most effective means of reducing costs in the supply chain.

The FL-BDDF framework's modular architecture and hybrid integration of BDA and Fuzzy Logic make it extremely scalable for large-scale supply chain networks with different product categories. The capacity to handle massive volumes of diverse data in parallel is a key feature of Big Data technologies like distributed computing frameworks (like Hadoop and Spark) that guarantee scalability over large networks. Fuzzy Logic is flexible enough to accommodate new product categories and regulations with little development effort. Even as complexity increases, the framework's capacity to preprocess and reduce high-dimensional input guarantees efficient computing.

In sectors such as retail, the framework may be used to forecast demand for seasonal items by combining real-time sales data with social media trends and weather patterns. This allows for better inventory

management and lessens the chances of overstocking or running out of stock. The framework helps improve production scheduling and minimize operating costs in manufacturing by forecasting demand variations for varied product categories. The FL-BDDF framework outperforms competing methods in flexibility because of its BDA and Fuzzy Logic components, which efficiently handle ambiguity and uncertainty and analyze large, dynamic information in real time.

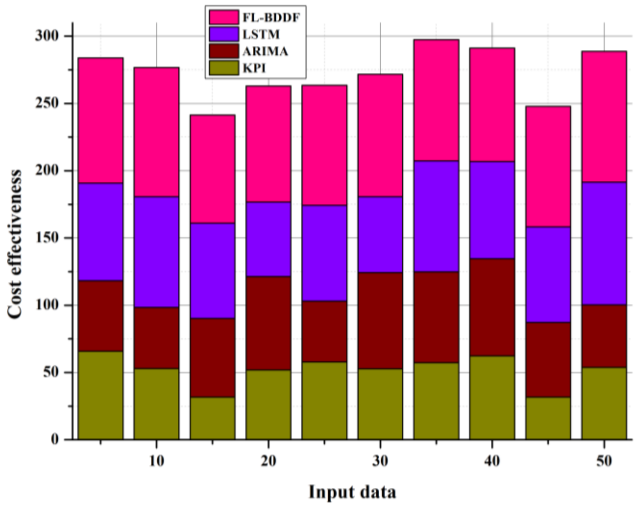

Fig. 8. Reduced costs.

9 | Conclusion

Prediction is an essential part of a supply chain, as plans at all levels of management rely on predictions. Forecasts are used in buying, operations, marketing, and finance departments. Supply chain forecasting is particularly crucial because the outcomes influence every link in the network. As a result, participants in the supply chain adopt a collaborative planning, forecasting, and restocking strategy to improve the chain's performance. Big Data and Fuzzy Logic demand forecasting enhances supply chain performance. Some have suggested that the organization's capacity to make decisions may be improved by incorporating FL-BDDF into the supply chain. Several parts of SCM may benefit from Big Data and Fuzzy Logic, including planning, delivery, manufacturing, development, and product returns. Data collected from Big Data helps the company predict the demand and value of the market. As a result, the company's bottom line would be significantly boosted, and product waste would decrease.

Furthermore, BDA for demand forecasting might significantly enhance the business supply chain performance. Small and medium-sized firms may benefit from collecting and analyzing large volumes of data from several sources to better manage inventory levels and supply chain operations. This Data enables more accurate and timely projections of client demand. Cost savings, more efficiency, and happier customers are all possible outcomes. However, businesses should consider the ethical and privacy implications before using consumer data for demand forecasting. Seeing how hotel SCM approaches are altered will be fascinating as BDA develops. In future research, we may compare the prediction accuracy of various fuzzy and non-fuzzy methods by applying them to the same forecasting issue.

Author Contributaion

S. B.: Methodology, Data collection and analysis, Writing – original draft.

A. M.: Conceptualization, Writing – review & editing.

B. V.: Methodology, Data interpretation.

G. M.: Data collection, Analysis.

K. N.: Project administration, Writing – review & editing.

S. S.: Supervision.

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Data Availability

No data is generated during this research.

Conflicts of Interest

The authors declare no conflict of interest.

Reference

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